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published in
Ecological Indicators
2020

DOI (link to publisher)
10.1016/j.ecolind.2020.106835

Ecological Indicators 119 (2020) 106835

Contents lists available at ScienceDirect

Ecological Indicators

journal homepage: www.elsevier.com/locate/ecolind

Projecting future impacts of cropland reclamation policies on carbon storage

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ARTICLE INFO

Keywords:
Cropland reclamation policies
Carbon storage
Optimization strategies
Cropland protection
Land use model

ABSTRACT

Cropland reclamation policies result in carbon storage loss by the conversion of natural land. However, the future impacts of cropland reclamation policies (CRP) on carbon storage have seldom been explored. Taking Hubei, China as study area, this study assesses the impacts of cropland reclamation policies before and after optimization on carbon storage from 2010 to 2030. The LAND System Cellular Automata model for Potential Effects (LANDSCAPE) was used to simulate the land use patterns in 2030, while the Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) Carbon Storage and Sequestration model was applied to calculate the changes in carbon storage. Results indicate that carbon storage loss due to cropland reclamation policies is expected to increase from 0.48 Tg·C to 4.34 Tg·C between 2010 and 2030 in Hubei. This increase is related to the loss of wetland and forest. Carbon storage loss can be reduced by 52%–73% by protecting carbon-rich lands. This study highlights the importance of considering the carbon storage loss when implementing cropland reclamation policies.

1. Introduction

Massive carbon emission is the primary cause of global warming and thus poses risks for human and natural systems (IPCC, 2014; Tokarska and Gillett, 2018). Currently, the global mean surface temperature is expected to increase by 1.5 °C between 2030 and 2050 (IPCC, 2018). Carbon storage can play an important role in mitigating global warming (He et al., 2016; Zhang et al., 2017) and this is strongly affected by land use (Guo and Gifford, 2002; Post and Kwon, 2000; de Souza Medeiros et al., 2020). Policies that steer land-use practices are thus likely to influence global warming (Geneletti, 2013; Bateman et al., 2013) and should be considered with care. This is a particularly complex issue as land-use policies typically result in direct and indirect changes in land use and greenhouse gas emissions (Wicke et al., 2012). An example of these indirect impacts is offered by cropland reclamation policies that aim to preserve the amount of cropland that otherwise would be lost to, for example, urban development (Stoms et al., 2009; Song and Pijanowski, 2014; Ke et al., 2018). Their direct impact of limiting the loss of cropland is often associated with an indirect loss of natural areas as these are converted to compensate for the cropland that is lost to urban development.

Given that global population is expected to increase in the future (Godfray et al., 2010; United Nations, 2017), cropland reclamation policies are vital to maintaining food security for two reasons. First of all, the demand for global food is predicted to increase by 60%–110% by the year 2050 (Godfray et al., 2010), so an additional 2 billion hectares may be needed to meet the increased demand for food and nutrition (Tilman et al., 2011). In addition, the projected population growth will result in an urban area expansion that is likely to claim some of the world's most productive croplands especially around the larger cities in Asia and Africa (Bren d'Amour et al., 2017).

Previous studies indicated that cropland reclamation policies (CRP) that call for a compensation of lost cropland, have effectively alleviated the reduction of cropland and helped control the impacts of urban expansion (Song and Pijanowski, 2014; Liang et al., 2015; Wang et al., 2018). Although the quantity of cropland can be maintained, the quality of cropland is often degraded since the cropland lost to urban development tends to have a higher quality than the reclaimed cropland (Lichtenberg and Ding, 2008; Liu et al., 2015). Furthermore, studies found that cropland reclamation policies threaten ecosystem services by occupying ecologically valuable land (Tan et al., 2005; Zheng et al., 2019a; Ke et al., 2019) such as forest, grassland, and wetland (IUCN, 2013). Recent eco-environmental impacts of implemented policies have been assessed for various countries (Tan et al., 2005; Lark et al., 2015; Shen et al., 2017; Garibaldi et al., 2019). Potential future impacts of cropland reclamation policies, however, have received less

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https://doi.org/10.1016/j.ecolind.2020.106835
Received 11 February 2020; Received in revised form 14 June 2020; Accepted 7 August 2020
Available online 18 August 2020
1470-160X/

attention and these are especially important in view of the ambitions to mitigate climate change through carbon storage. This issue is particularly relevant in China were strict cropland reclamation policies were implemented in 1997 to maintain food security (Liang et al., 2015; Wang et al., 2018) and the expected growth in population and associated urban expansion are likely to claim up to 71,000 km^2 – 86,000 km^2 of cropland until 2030 (Bren d'Amour et al., 2017). The policies state that new cropland should be reclaimed to compensate for the lost cropland (Liang et al., 2015; Wang et al., 2018).

Taking Hubei, China as case study area, we assess the future impacts of current cropland reclamation policies on carbon storage between 2010 and 2030. The latter year is considered to be China's turning point in population growth with its number of inhabitants peaking at 1.45 billion and its urbanization level reaching 70% (World Bank, 2012; Sun et al., 2016). Firstly, the land use in 2030 in scenarios with and without cropland reclamation policies is simulated. Secondly, carbon storage in 2010 and 2030 for both scenarios is calculated to assess the impact of the proposed policies. Finally, optimized cropland reclamation policies are proposed to reduce the expected loss in carbon storage.

2. Study area

Hubei is located in central China and has a total area of around 186,000 km^2 (Hubei Bureau of Statistics, 2019). The western, eastern, and northern parts are mainly covered with forest, while the central areas are dominated by cropland, wetland, and urban land (Fig. 1). Urban expansion in Hubei has taken large amounts of cropland in the past 20 years, while cropland reclamation resulted in the loss of natural land to compensate for the loss of cropland (Ke and Tang, 2019; Tang et al., 2020). Around 75% of urban expansion took place on cropland between 2000 and 2010, while 76% of cropland reclamation was from natural land (Tang et al., 2020). The urbanization level in Hubei is projected to increase to 66% in 2030 (Hubei Provincial People's Government, 2019). So, urban expansion will continue to claim cropland and with current cropland reclamation policies, this will result in a loss of natural land and ecosystem services. It is expected that the conflict between cropland reclamation policies and the conservation of ecosystem services will intensify with the projected rapid urban development in the future (Tilman et al., 2011).

3. Methods and data

3.1. Research framework

The research framework consists of two subsequent parts: assessing the impacts of current cropland reclamation policies on carbon storage between 2010 and 2030 (Fig. 2) and developing a more optimal policy that limits carbon storage loss (Fig. 3).

To quantify the impact of cropland reclamation policies on carbon storage (Fig. 2), we compared the carbon storage in future scenarios with and without cropland reclamation policies by combining a land-use model with a carbon storage assessment model. First, the LAND System Cellular Automata model for Potential Effects (LANDSCAPE, see Ke at al., 2017, 2018) is calibrated based on land use data for 2000 and 2010. Then, scenarios with and without cropland reclamation policies were developed and implemented in the LANDSCAPE model to generate land-use maps for 2030. The *Cropland Reclamation Policies* (CRP) scenarios assume that lost cropland will be compensated by converting other land-use types to cropland. To test the impact of increasing amounts of compensation we developed 10 scenario alternatives in which lost cropland is compensated by 10% increments until full compensation is achieved. The *No Cropland Reclamation Policies* (No_CRP) scenario acts as a reference and assumes the policy is not adopted. To make scenarios comparable, the amount of urban land in 2030 in all scenarios was set as 2423 km^2 as was predicted by the Case-Based Reasoning method (Zheng and Ke, 2018). Finally, carbon storage in 2010 and 2030 in these scenarios was assessed by the Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) Carbon

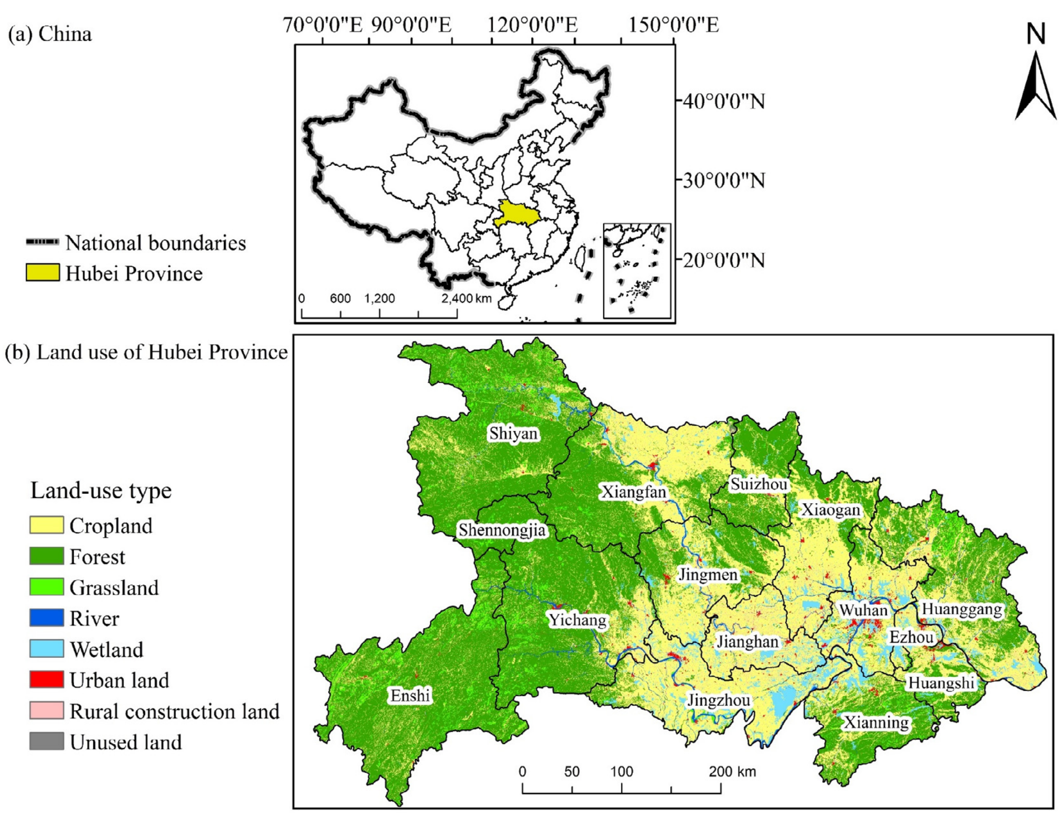

Fig. 1. Overview of Hubei Province, China: (a) the location of Hubei Province in China and (b) the land use of Hubei Province in 2010.

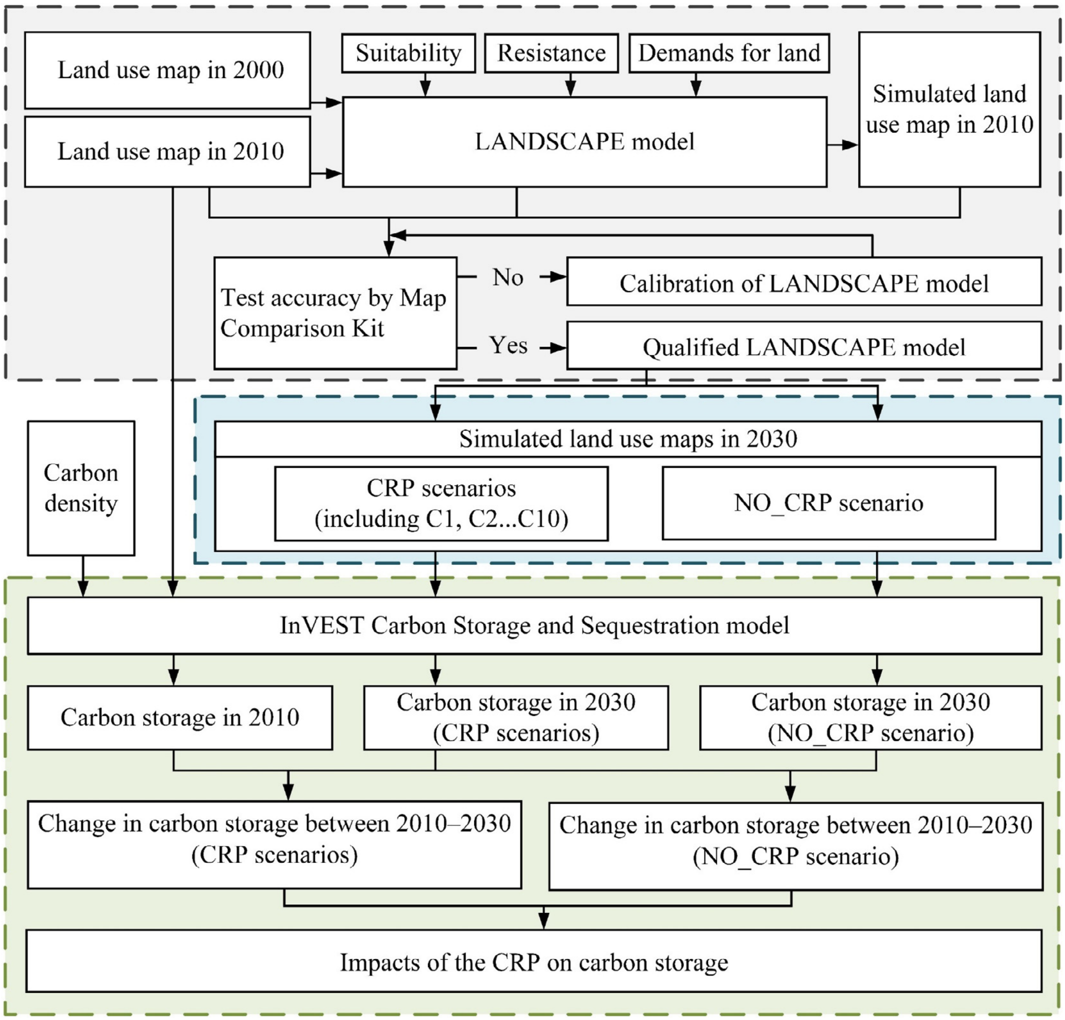

Fig. 2. Research framework of projecting future impacts of the *Cropland Reclamation Policies* (CRP) scenarios on carbon storage (referred to as C1, C2, …C10 in which lost cropland is compensated for 10%, 20%, …100%, respectively) and the *No Cropland Reclamation Policies* (No_CRP) scenario.

Storage and Sequestration model (Sharp et al., 2015; He et al., 2016).

To limit the impact on carbon storage we also developed optimized cropland reclamation policies and assessed their impact compared to the current policies (Fig. 3). First, the *Optimized Cropland Reclamation Policies* (OP_CRP) scenarios were defined that assume cropland reclamation policies are implemented in combination with the prioritized protection of carbon-rich land. Key in these scenarios is the adjusted resistance of carbon-rich land-use types based on their carbon density (as described in Section 3.2.1). The 2030 land use for these scenarios was also simulated by the LANDSCAPE model. Subsequently, carbon storage between 2010 and 2030 in the optimized scenarios was calculated and compared to that in the current policies.

3.2. Methods

3.2.1. LANDSCAPE model for land use simulation

Cellular Automata (CA) models are the most commonly applied land-use change models since their inception in the 1980s (see, for example, Couclelis, 1985; White and Engelen, 1997; Batty et al., 1999). They are efficient and effective tools to simulate land-use change and recent applications range from the regional scale (Berberoğlu et al., 2016; Martellozzo et al., 2018) to the global scale (Li et al., 2016). The LANDSCAPE model applied in this study is an improved CA-based model that is also applicable to different regions of the world (Ke et al., 2017). The main advantage of the model is its capability to simulate cascading processes of land-use change in which one process initiates another (Ke et al., 2017; Zheng et al., 2019ab). This is essential in our case as we face the conversion of cropland into urban land that results in the transition of natural land into cropland. The allocation of land-use types is determined by two factors: suitability and resistance (Ke et al., 2018). Suitability represents the quality of the location for a target land-use type, and resistance represents the difficulty for a cell to convert from the current land-use type to another one (Ke et al., 2018). The combined effect of suitability and resistance is calculated according to:

$$TTP_{l,tu} = \frac{S_{l,tu}}{R_{l,cu}} \tag{1}$$

where $TTP_{l,tu}$ is the total transition possibility of a cell at location l for the target land-use type*tu*; $S_{l,tu}$ is the suitability for a cell at location l for the target land-use type tu, and is the resistance of a cell at location l to convert from the current land-use type cu to another land-use type (Zheng et al., 2019a).

Suitability $S_{l,tu}$ is calculated according to:

$$S_{l,tu} = (1 + (-ln\gamma)^{\alpha}) \times PSC_{l,tu} \times Con(C_{l,tu}) \times NL_{l,tu} \tag{2}$$

where $1 + (-ln\gamma)^{\alpha}$ represents a random factor used to explain the impacts of factors not included in the model on the dependent variable (in which γ is a stochastic number which varies from 0 to 1 and α is an integer from 0 to 10 used as a dispersion factor to control the random

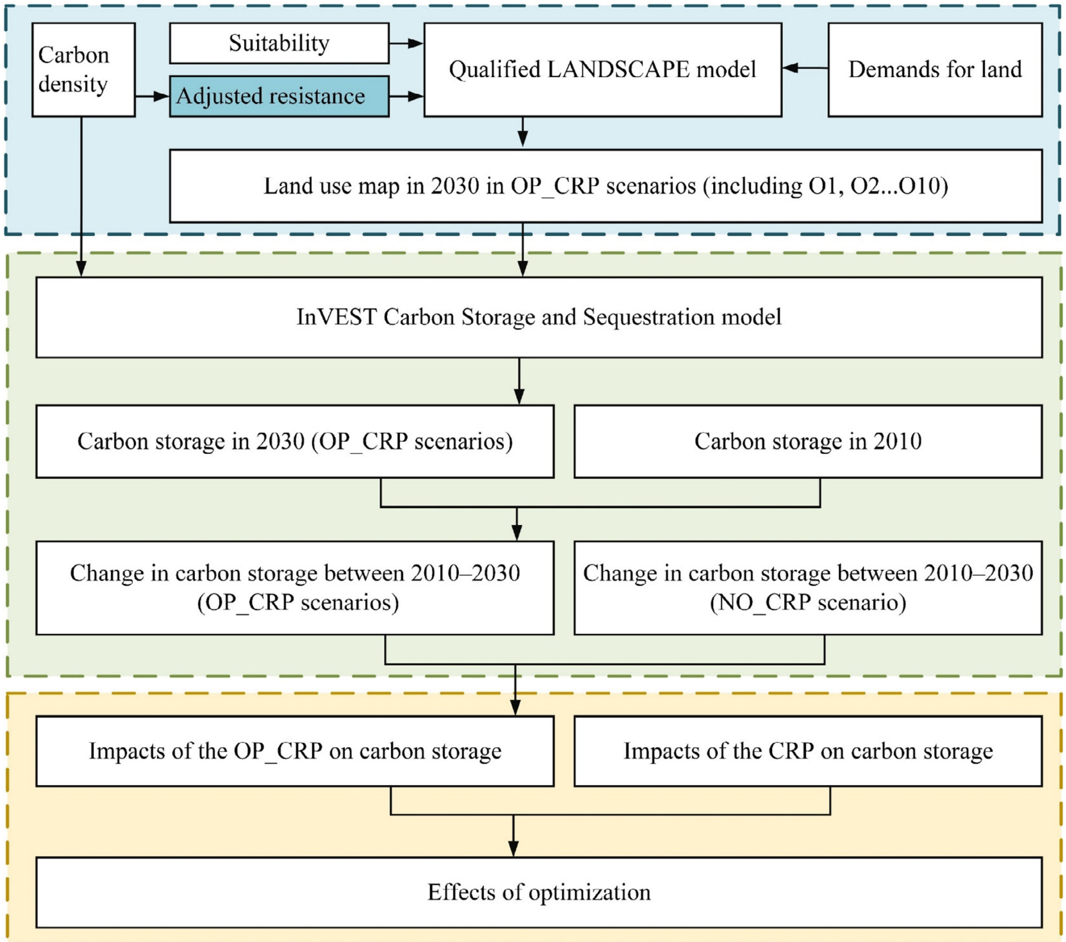

Fig. 3. Research framework of exploring the effects of the *Optimized Cropland Reclamation Policies* (OP_CRP) scenarios on carbon storage (referred to as O1, O2…O10 in which lost cropland is compensated for 10%, 20%, …100%, respectively).

number) (Zheng et al., 2019a). $PSC_{l,tu}$ represents the impacts of physical and socioeconomic characteristics at location l on suitability, such as elevation, slope, soil, and the distance to roads, etc. $PSC_{l,tu}$ was calculated by Support Vector Machines (SVM) (Ke et al., 2017). $Con(C_{l,tu})$ represents the constraint value of a cell, with a value of 0 for cells that are unchangeable, or a value of 1 for cells that can change. The $Con(C_{l,tu})$ value of river was set as 0 since the river in both the location and area was stable according to the land-use maps of Hubei in 2000 and 2010.$NL_{l,tu}$ represents the impacts of neighboring land-use types, which is calculated following:

$$NL_{l,tu} = \frac{n(SC = tu)}{TN} \tag{3}$$

where $n(SC = tu)$ represents the number of cells that represent the type of target land use in a given neighborhood at location l, and TN represents the total number of cells in the given neighborhood.

The resistance to land-use change can be calculated based on the observed land-use maps (Ke et al., 2017; Zheng et al., 2019a). The resistances in this study (Table 1) were calculated following the method of Ke et al. (2017) that was also applied in the studies of Mei et al. (2017), Ke et al. (2018, 2019), and Zheng et al. (2019a,b).

To limit the conversion of carbon-rich land-use types in OP_CRP scenarios, the resistance in the LANDSCAPE model was adjusted according to their total carbon density following:

$$R_i^{'} = R_i \times \left[\frac{CD_i - CD_{min}}{CD_{max} - CD_{min}} \times (R_{max} - R_{min}) + R_{min} \right] \tag{4}$$

where$R_i^{'}$ is the adjusted resistance of land-use type i. R_i is the original resistance of land-use type$i$. CD_i is the total carbon density of land-use type i. CD_{max} represents the maximum value of carbon density, while CD_{min} represents the minimum one. R_{max} represents the maximum value of resistance, andR_{min} represents the minimum one (Zheng et al., 2019b).

3.2.2. Calibration of LANDSCAPE model

Kappa Simulation (Visser and De Nijs, 2006) was used to test the accuracy of the LANDSCAPE model by comparing simulated land use for 2010 with the observed land-use in 2010. The KSimulation represents the degree of agreement in values ranging from −1 to 1; with positive values indicating a relatively high accuracy of the model (van Vliet et al., 2011). KSimulation values of each land-use type in this research were larger than 0 (Table 2), which indicates the LANDSCAPE

Table 1
Resistance to land-use change for each land-use type.

	Cropland	Forest	Grassland	River	Wetland	Urban land	Rural construction land	Unused land
Resistance value	1.00	1.25	1.25	1.50	1.25	1.50	1.50	1.00

Table 2
Kappa Simulation values of LANDSCAPE model.

	Cropland	Forest	Grassland	Wetland	Urban land	Rural construction land	Unused land
KSimulation	0.333	0.140	0.218	0.270	0.521	0.298	0.296

model is qualified for further simulations.

3.2.3. InVEST model for carbon storage assessment

The InVEST Carbon Storage and Sequestration model has the advantages of simple requirement of input parameters and spatial visualization of the results (Sharp et al., 2015; He et al., 2016; Zhao et al., 2019). Hence, the model has been widely used to estimate carbon storage in case studies around the world (Nelson et al., 2010; Chaplin-Kramer et al., 2015; Zhang et al., 2017). The spatial distribution of carbon storage can be easily obtained by inputting land use maps and carbon densities of each land-use type (Sharp et al., 2015). The sum of carbon storage can be calculated accordingly:

$$C_{sum} = \sum_{1}^{i} (C_{i\_above} + C_{i\_below} + C_{i\_soil} + C_{i\_dead}) \times A_i, (i = 1, 2, ..., n) \quad (5)$$

where C_{sum} is the sum of carbon storage of all land-use types; C_{i_above}, C_{i_below}, C_{i_soil}, and C_{i_dead} are the carbon densities of aboveground mass, belowground mass, soil organic matter, and dead organic matter in land-use type i, respectively; A_i is the area of land-use type i.

3.3. Data

3.3.1. Datasets for land-use change simulation

Current land-use patterns, climatic conditions, physical characteristics, and accessibility are key factors determining the suitability for land-use change (Ke et al., 2017; Zheng et al., 2019ab). Table 3 lists the datasets that were included in our calculations of land-use suitability. All datasets were transformed to rater format and aggregated or resampled into the same 100 m spatial resolution to allow combination (Ke et al., 2018; Zheng et al., 2019a).

The initial land use data with a spatial resolution of 30 m were extracted from remote sensing images (Landsat TM/ETM). The initial 25 land-use types were reclassified into eight main categories (see Table 3). The meteorological data described spatial variation in annual rainfall and temperature. Based on the highly detailed elevation data the local slope could be calculated. Given that soil conditions are important factors affecting agricultural land conversion (Piquer-Rodríguez et al., 2018), the indicators listed in Table 3 were selected in line with similar research (Ke et al., 2018; Zheng et al., 2019ab). The original soil data were at a scale of 1:1,000,000 and also converted to raster data. Accessibility was described as Euclidean, overland distances (Liberti et al., 2014) to different types of infrastructure. This approach is very effective to characterize regional variation in the density of the road network and also applied in similar research (Ke et al., 2018; Zheng et al., 2019ab).

3.3.2. Carbon densities of land-use types

The InVEST Carbon Storage and Sequestration model contains four components that refer to the carbon density of land-use types: carbon densities in aboveground biomass, belowground biomass, soil organic matter, and dead organic matter (Sharp et al., 2015). In this research, the carbon density for each land-use type was obtained from existing literature that applied scientific methods (e.g., field survey and geochemical experiment) to measure carbon density (Table 4).

4. Results

4.1. Cropland reclamation in different scenarios

In the NO_CRP scenario, the total loss of cropland due to urban expansion is predicted to be 252 km^2. In the CRP scenarios, cropland reclamation was set to compensate the lost cropland by 10% (25.2 km^2), 20% (50.4 km^2), …100% (252 km^2) in C1, C2, …C10, respectively (Fig. 4). The dominant source of cropland reclamation is expected to be wetland (78%–88%), followed by forest. The amount of wetland converted to cropland is projected to increase significantly (from 22.1 km^2 to 197.3 km^2), while that of the forest is expected to increase only slightly (from 2.8 km^2 to 54.0 km^2). Comparatively, the amount of grassland converted to cropland is anticipated to be much less, while that of unused land is expected to be minimal as these are relatively rare in the region; grassland accounts for 4% of the total area, while that of unused land takes up only 0.03%.

In the OP_CRP scenarios, the main source of cropland reclamation is expected to be forest (accounting for 64%–68%), followed by wetland (Fig. 5). All sources of cropland reclamation are anticipated to increase, especially forest and wetland. Specifically, the amount of forest converted to cropland is anticipated to increase from 16.9 km^2 to 163.0 km^2 while that of the wetland is expected to increase from 3.8 km^2 to 73.5 km^2.

Table 3
Datasets used for land-use change simulation.

Dataset (resolution/scale)	Data description (units)	Data source
Land use data (30 m)	Land use maps of Hubei in 2000 and 2010 (8 main categories: cropland, forest, grassland, river, wetland, urban land, rural construction land, and unused land*)	Data Centre of Resources and Environment, Chinese Academy of Science (CAS)
Meteorological data (0.5°×0.5°)	Annual rainfall (mm)	The Chinese Meteorological Administration (CMA)
	Annual accumulated temperature (°C), i.e. the sum of average daily temperatures above 10 °C	
Terrain data (90 m)	Elevation (m)	The Shuttle Radar Topography Mission (SRTM)
	Slope (degree)	
Soil data (1:1,000,000 scale)	Soil pH value	The China Soil Database
	Soil plough thickness (cm)	
	Soil organic content (%)	
	Soil phosphorus content (%)	
Accessibility data (1:25,000 scale)	Euclidean distance to the nearest national road, provincial road, main road, minor road, highway, railway, and other road (m)	The Traffic Atlas of Hubei

* Unused land includes sandy land, Gobi, saline, bare soil, bare rock, alpine desert, and permanent ice and snow (Liu et al., 2019).

Table 4
Carbon density of each land-use type in Hubei (Mg/hm^2).

Land-use types	Above-ground biomass	Below-ground biomass	Dead organic matter	Soil organic matter	Total carbon density	References
Cropland	16.49	10.89	2.11	75.82	105.31	Li et al. (2020); Ke and Tang (2019); Chuai et al. (2013)
Forest	30.14	6.03	2.78	100.15	139.1	Li et al. (2020); Ke and Tang (2019); Chuai et al. (2013)
Grassland	14.29	17.15	2.42	87.05	120.91	Li et al. (2020); Ke and Tang (2019); Chuai et al. (2013)
River	0.00	0.00	0.00	0.00	0.00	Liu et al. (2019); Ke and Tang (2019)
Wetland	14.21	7.89	9.47	284.19	315.76	Xiao et al. (2019); Ke and Tang (2019)
Urban land	7.61	1.52	0.00	34.33	43.46	Li et al. (2020); Ke and Tang (2019); Xi et al. (2013)
Rural construction land	7.61	1.52	0.00	34.33	43.46	Li et al. (2020); Ke and Tang (2019); Xi et al. (2013)
Unused land	10.36	2.07	0.96	34.42	47.81	Li et al. (2020); Ke and Tang (2019); Xi et al. (2013)

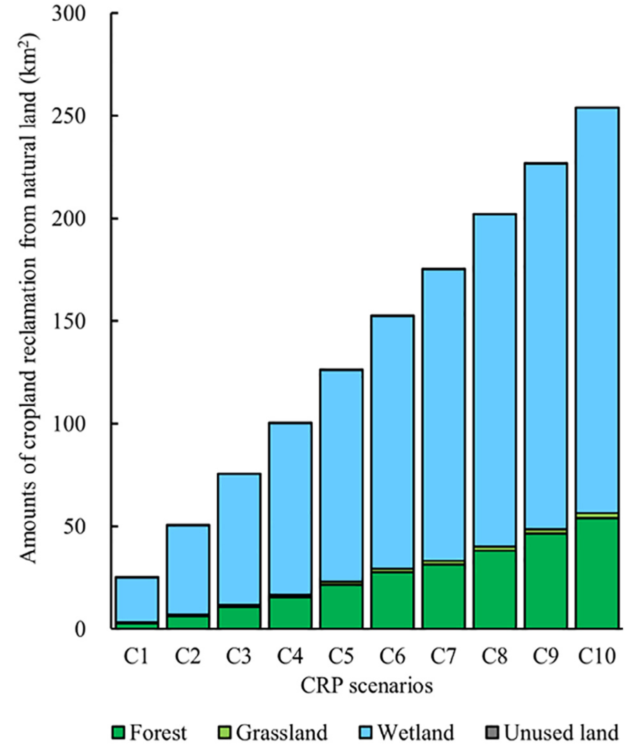

Fig. 4. Cropland reclamation from natural land between 2010 and 2030 in Hubei in CRP scenarios.

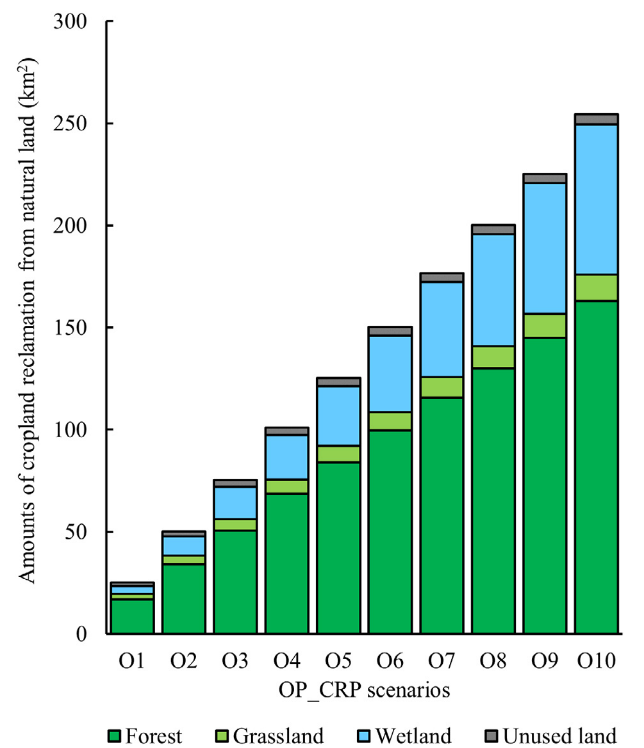

Fig. 5. Cropland reclamation from natural land between 2010 and 2030 in Hubei in the OP_CRP scenarios.

4.2. Impacts of CRP on carbon storage

Carbon storage loss caused in the CRP scenarios is predicted to continuously increase from 0.48 Tg·C to 4.34 Tg·C with the increase of cropland reclamation (Fig. 6). Noticeably, the contribution of

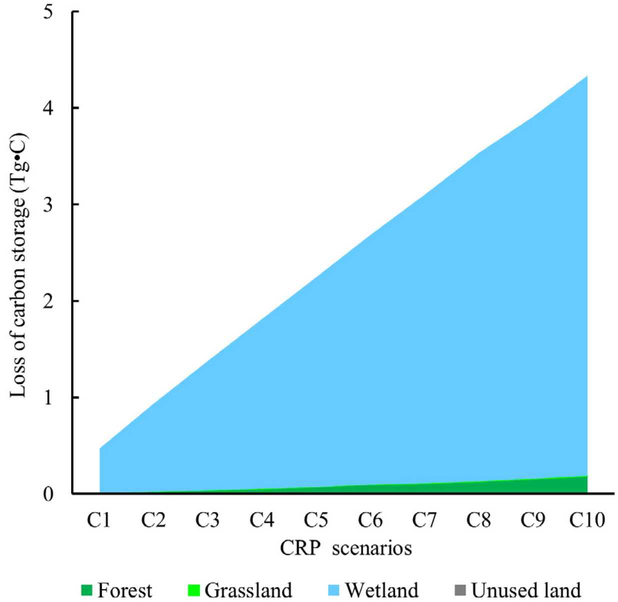

Fig. 6. Carbon storage loss between 2010 and 2030 in Hubei in the CRP scenarios.

converting wetland to cropland on carbon storage loss is anticipated to rank highest, accounting for 96%–98%, followed by the contribution of converting forest. Comparatively, converting grassland and unused land to cropland is expected to have almost no effect on carbon storage loss.

Carbon storage loss caused in the OP_CRP scenarios is expected to increase from 0.13 Tg·C to 2.09 Tg·C (Fig. 7). Specifically, converting wetland to cropland is predicted to result in carbon storage loss from 0.08 Tg·C to 1.55 Tg·C. Comparatively, carbon storage loss caused by converting forest is projected to be relatively small (ranging from 0.06 Tg·C to 0.55 Tg·C). Meanwhile, the contribution of converting wetland to cropland on carbon storage loss is projected to increase from 61% to 74%, while that of converting forest is projected to decrease from 44% to 26%.

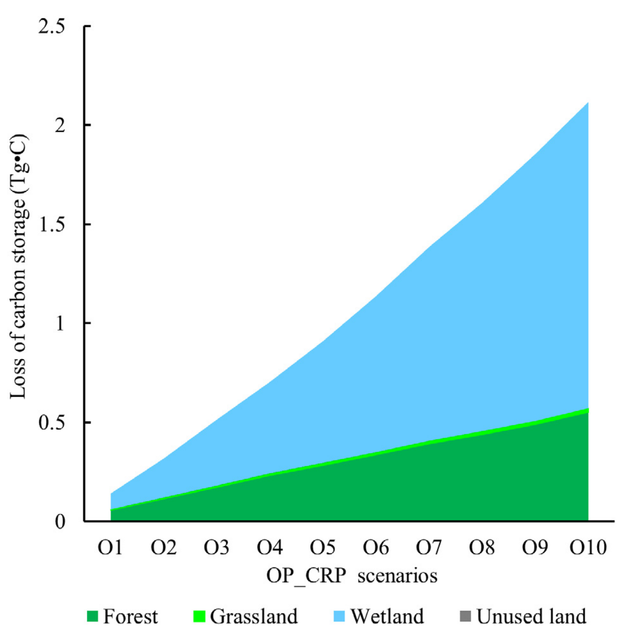

Fig. 7. Carbon storage loss between 2010 and 2030 in Hubei in the OP_CRP scenarios.

4.3. Optimization effects in reducing carbon storage loss

After optimization, the amount of carbon storage loss between 2010 and 2030 is anticipated to decrease by 0.35 Tg·C–2.25 Tg·C (Fig. 8). Carbon storage loss is thus projected to be reduced by 52%–73% by optimization.

Carbon storage loss is predicted to decrease in most regions of Hubei after optimization between 2010 and 2030 (Table 5). The decrease is projected to be greatest (with 0.56 Tg·C) in Jingzhou, where 54% of carbon storage loss will be reduced by optimization. In contrast, carbon storage loss in Enshi and Shiyan is anticipated to slightly increase (less than 0.03 Tg·C). This is related to differences in the type and distribution of natural land. Forest and grassland concentrate in the west of Hubei, especially in Enshi and Shiyan (where there is almost no wetland). The loss in wetland is expected to be reduced after optimization, while the loss of other types of natural land, such as forest and grassland, is projected to increase.

5. Discussion

Existing studies documented that cropland reclamation policies have had negative effects on ecosystem services in the past (Tan et al., 2005; Lark et al., 2015; Shen et al., 2017; Garibaldi et al., 2019). However, its impact on carbon storage in the future is rarely explored. This study showed that cropland reclamation policies are likely to result in a considerable carbon storage loss until 2030 in the Chinese province of Hubei. This carbon storage loss increases linearly with the amount of cropland. Previous studies demonstrated that carbon storage loss due to cropland reclamation is especially related to the loss of forest and wetland (Johnson et al., 2014; Chaplin-Kramer et al., 2015; Mao et al., 2018). This study suggests that similar developments are likely to occur in the case study region: the conversion of wetland and forest is projected to contribute most to carbon storage loss. This results from that the large amounts of wetland and forest that are expected to be converted into cropland and their relatively high carbon density. The integrated land-use and carbon storage modelling approach applied in this study can also be applied in other regions to assess the potentially negative indirect effect of cropland reclamation policies on carbon storage and thus help prevent such adverse effects. As demonstrated in this paper, the modelling approach can also be used to develop alternative cropland reclamation policies that are more sensitive to carbon loss and assess their potential impact.

Since carbon storage loss due to cropland reclamation policies is anticipated to be considerable in the future, we should rethink cropland protection policies related to cropland reclamation, such as the *Requisition–Compensation Balance of Cropland Policy* and the *General Dynamic Balance of Cropland Policy in China* (Liu et al., 2017). Specifically, the *Requisition–Compensation Balance of Cropland Policy* clarifies that cropland reclamation needs to compensate for the lost cropland (Chen et al., 2018; Yu et al., 2018). Meanwhile, the *General Dynamic Balance of Cropland* (Liu et al., 2017; Wu et al., 2017) aims to keep a balance between the amount of occupied cropland and cropland reclamation. The principal target of these cropland protection policies focuses on maintaining the total amount of cropland by cropland reclamation (Liu et al., 2017), which inevitably leads to considerable loss of natural land (Wu et al., 2017) and carbon storage. In this case, it is necessary to pay more attention to the carbon storage loss and other ecosystem services when implementing the cropland protection policies related to cropland reclamation.

The optimized strategy introduced in this study can significantly reduce carbon storage loss by protecting the land with high carbon density. Given that the cropland reclamation has been identified as the primary reason for more than 50% loss of original wetland (Verhoeven and Setter, 2009), the approach and framework applied in this optimized strategy can provide valuable perspective for the conservation of carbon storage service worldwide. Meanwhile, ecological conservation

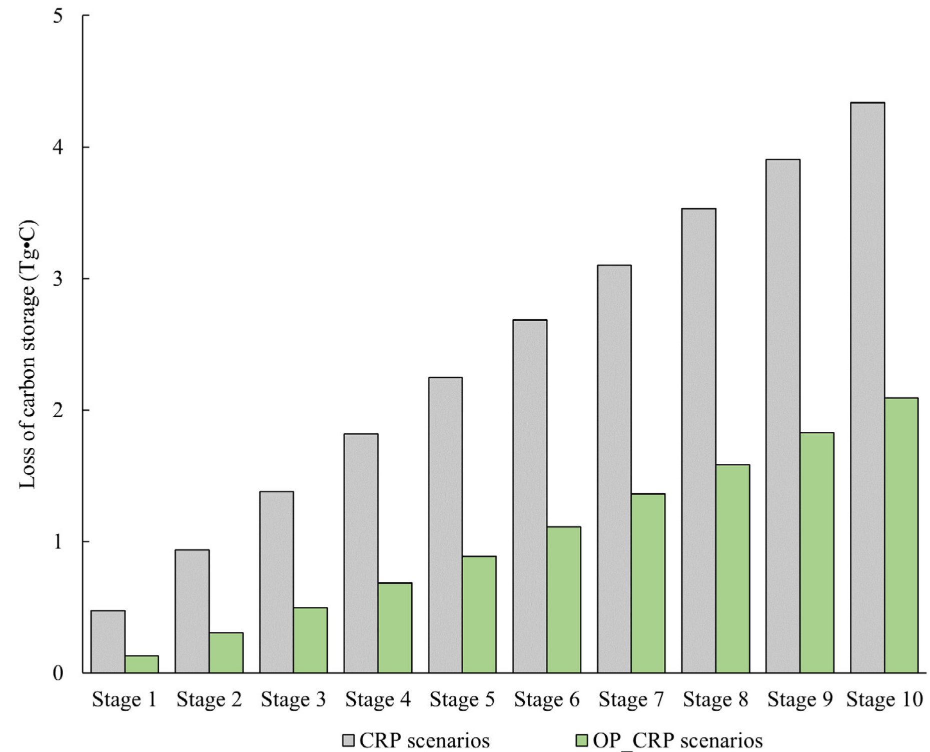

Fig. 8. Optimization effects in reducing carbon storage loss between 2010 and 2030 in Hubei. Stage 1, Stage 2, …, and Stage 10 are the stages when the cropland is compensated 10%, 20%, …, and 100%, respectively.

Table 5

The reduction of carbon storage loss after optimization in each region of Hubei (Tg·C).

	Stage1	Stage2	Stage3	Stage4	Stage5	Stage6	Stage7	Stage 8	Stage 9	Stage 10
Jingzhou	0.08	0.15	0.22	0.27	0.33	0.38	0.43	0.48	0.50	0.56
Jianghan	0.05	0.09	0.12	0.16	0.19	0.23	0.26	0.31	0.33	0.35
Jingmen	0.04	0.09	0.14	0.19	0.24	0.26	0.28	0.31	0.32	0.35
Xiangfan	0.06	0.11	0.15	0.18	0.19	0.22	0.25	0.28	0.29	0.33
Xiaogan	0.05	0.09	0.12	0.16	0.19	0.22	0.24	0.26	0.29	0.28
Wuhan	0.04	0.07	0.09	0.11	0.13	0.14	0.15	0.17	0.19	0.20
Huanggang	0.01	0.01	0.01	0.01	0.02	0.03	0.03	0.04	0.05	0.06
Xianning	0.01	0.01	0.01	0.02	0.03	0.03	0.03	0.04	0.04	0.04
Suizhou	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.02
Yichang	0.01	0.01	0.01	0.01	0.02	0.02	0.03	0.03	0.03	0.04
Ezhou	0.00	0.01	0.01	0.02	0.03	0.03	0.03	0.04	0.04	0.05
Huangshi	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02
Shennongjia	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Enshi	0.00	0.00	0.00	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
Shiyan	0.00	-0.01	-0.01	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.03
Total reduction	**0.35**	**0.64**	**0.89**	**1.12**	**1.36**	**1.56**	**1.73**	**1.96**	**2.08**	**2.25**

* The green zone indicates that carbon storage loss reduces after optimization and the darker the color, the greater the reduction. In contrast, the grey zone represents that the carbon storage loss increases after optimization. Stage 1, Stage 2, …, and Stage 10 are the stages when the cropland is compensated 10%, 20%, …, and 100%, respectively.

measures should be taken to mitigate and even avoid natural land loss due to cropland reclamation. For example, the strategy of Ecological Conservation Redlines (ECRs) adopted in China aims to achieve ecological security and nature conservation (Jiang et al., 2019).

The limitations of our study include several aspects. First, the carbon density adopted in this study was from the published literature instead of the biogeochemical method or sampling method. Performing additional field experiments could help to generate more accurate, region-specific results. Secondly, the InVEST Carbon Storage and Sequestration model ignores spatial and temporal heterogeneity of carbon density for individual land-use types related to, for example, local soil conditions (Bruun et al., 2015), land management practices (Yu et al., 2020), and maturing of vegetation (Gao et al., 2016). A better understanding of the factors that result in this spatio-temporal heterogeneity would be extremely helpful to further improve carbon storage modeling (Liu et al., 2019). Finally, it should be acknowledged that while the proposed optimization strategy can provide a useful perspective for decision-makers to protect carbon storage, it may be difficult to implement these for that sole purpose. Instead, it may be more efficient and effective to incorporate such ambitions in more comprehensive, integrated ecosystem service protection policies.

6. Conclusions

This study indicates that cropland reclamation policies are predicted to have negative impacts on carbon storage, while the optimized cropland reclamation policies help to significantly reduce the carbon storage loss by protecting land-use types with high carbon density from being encroached by cropland reclamation. It is important to consider the trade-offs between cropland reclamation and carbon storage loss when making and implementing the cropland protection policies related to cropland reclamation. The modelling approach applied in this study proved to be helpful to enhance our understanding of future impacts of cropland reclamation policies on carbon storage and help develop effective optimization strategies. It can provide scientific evidence for decision-makers to reconcile cropland protection aimed at achieving food security with ecosystem services conservation.

CRediT authorship contribution statement

Lanping Tang: Conceptualization, Software, Investigation, Writing - original draft, Project administration. **Xinli Ke:** Conceptualization, Methodology, Supervision, Funding acquisition. **Qiushi Zhou:** Software. **Liye Wang:** Software. **Eric Koomen:** Conceptualization, Methodology, Writing - revision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work is supported by the National Natural Science Foundation of China [grant numbers 41971240 & 41371113], Post-finance Project for National Social Sciences [grant number 19FGLB071], Post-finance Project for Philosophy and Social Sciences of the Ministry of Education [grant number 18JHQ081], and Fundamental Research Funds for the Central Universities [grant number 2662017PY063]. The authors appreciate that Professor Chongfa Cai's contribution to knowledge about soil and vegetation. The authors appreciate that three anonymous reviewers proposed insightful comments to help us improve this paper.

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